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MBA PROFESSIONAL REPORT

Grade Point Average as a Predictor of Success in Explosive Ordnance Disposal Training

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December 2009

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13. ABSTRACT *(maximum 200 words)*

The purpose of this MBA Project was to determine if a student's Grade Point Average (GPA) while attending Naval School Explosive Ordnance Disposal (NAVSCOLEOD) is an accurate predictor of graduation. This project was conducted with the sponsorship and assistance of the Center for EOD and Diving, as well as NAVSCOLEOD. This project served to verify the graduation prediction model currently in use at NAVSCOLEOD is valid. The regression equation used in the graduation prediction model was updated with student data from 2004–2008.

NAVSCOLEODINST 5420.1U claims the model predicts successful completion of training for 95% of graduates who experienced a setback, and that the model is far more accurate overall than the traditional Academic Review Board (ARB) process. Based on student data from 2004–2008, the model predicted 94.1% would graduate and 5.9% would fail. This is not within the specified requirements of NAVSCOLEODINST 5420.1U.

We also conclude that the methodology used in the current graduation prediction model is not a true portrayal of student graduation or failure. This model proceeds from outcome to prediction, instead of the other way around. We discuss another approach that more logically proceeds from prediction to outcome and gives a clearer understanding of model accuracy.

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GRADE POINT AVERAGE AS A PREDICTOR OF SUCCESS IN EXPLOSIVE ORDNANCE DISPOSAL TRAINING

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Submitted in partial fulfillment of the requirements for the degree of

MASTER OF BUSINESS ADMINISTRATION

from the

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December 2009

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LIST OF ACRONYMS AND ABBREVIATIONS

ARB	Academic Review Board
DOR	Drop on Request
GPA	Grade Point Average
IEDs	Improvised Explosive Devices
LSI	Learning Styles Inventory
MIDAS	Multiple Intelligences Developmental Assessment Scales
NAVSCOLEOD	Naval School Explosive Ordnance Disposal
RFF	Request for Forces
TO	Training Officer
USA	United States Army
USAF	United States Air Force
USMC	United States Marine Corps
USN	United States Navy

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I. INTRODUCTION

The wars in Iraq and Afghanistan, coupled with President Bush's 2007-troop surge and President Obama's 2009-troop increase have had numerous ramifications for the military. These effects have impacted not only the coalition forces sent directly into combat, but also the multiple training pipelines required to support the request for forces (RFF). President Bush's deployment of an additional 21,500 troops to Baghdad and Al-Anbar province in March of 2007 increased total U.S. forces in the country to 135,000 (Iraq by the Numbers, 2007). President Obama's deployment of 17,000 additional troops in Afghanistan has put additional stressors on the military force. These new force requirements strain the EOD community that is undermanned in all four services.

Currently enlisted manning for Navy EOD is at 95% of authorized strength; however, Zone A manning (sailors who have 17 months to six years of service) is only 75 percent. The Air Force is manned at 80%, the Army at 84% and the Marine Corps at 78%, according to personal correspondence with respective service representatives. Keeping this highly trained force at capacity is a continual challenge as Improvised Explosive Devices (IEDs) continue to be the number one killer in the war on terror (JIEDDO, 2008). According to the Joint Improvised Explosive Device Defeat Organization's Annual 2008 Report, IEDs are the weapon of choice for terrorists worldwide. IED construction requires limited skill and gives the terrorist "the ability to conduct spectacular attacks for relatively small investment. IEDs continue to provide the enemy with inexpensive, stand-off, precision weapon systems that often provide the attacker with near total anonymity" (JIEDDO, 2008).

In calendar year 2006, total Joint EOD responses in combat zones totaled 20,890 (Wehmeyber, 2007). This number represents only one year of combat operations, while EOD technicians have been deployed since 2003 and deployments are ongoing. Year 2007 was the first time since the initial IED attack in 2003 that the number of annual IED incidents in Iraq began to decline. In 2008, IED accounted for only 40% of attacks on coalition forces in Iraq, reaching their lowest levels since 2003. "The total number of IED attacks in September 2008 was 33% of September 2007 and 22% of September 2006 levels" (JIEDDO, 2008). Although this decline is good news, the past five years of IED incidents have strained the EOD force as EOD technicians have been tasked with responding to each of these incidents. Even though IED incidents are decreasing in Iraq, they represent 75% of enemy initiated action in Afghanistan. According to JIEDDO, "by September 2008 total IED incidents in Afghanistan were roughly 25% higher than the number experienced during the previous year and twice the number in 2006" (JIEDDO, 2008).

EOD technicians train to combat the prime killer of coalition forces on the battlefield. Their missions include IED incidents, unexploded ordnance responses, route clearance convoys, direct action support and post-blast analysis. The scope of the EOD mission set is expanding as adversaries adapt and incorporate both low-tech and increasingly sophisticated technologies to wage war, e.g., bombs made from fertilizers, Internet recruiting, and cell-phone bomb activation. Deployment rates are at an all time high, with dwell time in the Air Force reaching 1:1, meaning technicians are deployed as often as they are home (Wehmeyber, 2007). Although the services offer various incentives, such as early promotion, re-enlistment bonuses and special duty assignment pays to EOD technicians, community manning remains insufficient to meet requirements. As individual services increase the number of students at EOD School to counter these manning shortfalls, attrition rates there are also a contributing variable to persistent low manning strength.

To become an Explosive Ordnance Disposal technician, each candidate, regardless of service affiliation, must complete an intensive training curriculum at Naval School Explosive Ordnance Disposal (NAVSCOLEOD), Eglin Air Force Base Florida. The program is both physically and mentally challenging, lasting at least 42 weeks, and possibly more, depending on service and training setbacks. An academic setback occurs when a student cannot complete the required learning objectives for a specific area of study and must repeat the training. The Navy has the longest training pipeline, 68 weeks, because of the inclusion of dive training, parachute training and tactical training

(Navy.mil, 2009). The attrition rate varies by service with the Air Force typically having the highest and the Marine Corps the lowest. The overall attrition rate has averaged 27% over the last five years (Andrea, 2009).

The training curriculum consists of 12 phases: 1) Core I, 2) Demolition, 3) Reconnaissance, 4) Tools and Methods, 5) Core II, 6) Ground Ordnance, 7) Air Ordnance, 8) Improvised Explosive Devices, 9) Biological and Chemical Weapons, 10) Nuclear Weapons, 11) Weapons of Mass Destruction, and 12) Underwater Ordnance. This last division is for naval personnel only. “Upon graduation, EOD technicians are equipped with the skills to render safe and dispose of explosive material in permissive and non-permissive environments” (Navy.mil, 2009). However, with an attrition rate approaching 30%, graduating is difficult and manning continues to suffer.

The increasing EOD force requirements in Iraq and Afghanistan, added to the existing manning shortfalls, have created a problem needing serious mitigation. One solution (and the premise behind this story) is to increase student throughput substantially at NAVSCOLEOD. From 2004 to 2008, billets at EOD School have increased from 777 students to 1,122 students, a 44% increase (Andrea, 2009).

The influx of personnel at the schoolhouse has caused a bottleneck effect when students have experienced a training setback and await an Academic Review Board (ARB). The ARB is designed to evaluate the student’s academic progress and make recommendations concerning student training potential. A setback is administered when students do not meet training objectives, most commonly evidenced in a written or practical exercise test failure. An ARB may be convened at any time if the division officer feels the student has become so far behind that training objectives will not be met for the division, or the student appears to reflect a safety hazard (NAVSCOLEOD, 2008).

Approximately 40% of students attending the 42-week curriculum receive at least one setback in training. (In years 2002–2007, there were 3,597 students and 1,391, roughly 39% of students, experienced at least one academic setback). An ARB convenes when a student fails both an initial test and the retest in any one of the 12 divisions. After two test failures in a row, the student is removed from training while the ARB convenes.

The ARB determines if the student will be allowed to repeat the division, or will be removed from training permanently. Typically, a student is granted one setback in training, but if a second ARB must be convened, the probability a student will graduate is low. Extensions in training are financially costly as they increase a student's total time in training. Non-graduation is even more costly as there is no return on investment on capital or manpower (NAVSCOLEOD, 2008).

The goals of the ARB include helping students solve problems that may prevent successful completion of training, as well as identifying which students are capable of completing the training. The ARB also determines which students are unwilling or unable to complete training and the board makes recommendations concerning its findings (NAVSCOLEOD, 2008). The policy states that:

> The Scope of Possible ARB Recommendations Includes:
>
> 1. <u>Continue with Class</u>: Continuation of training in the present class with or without remediation.
>
> A. Without Remediation: The student is not required to take a retest and the student has met all training objectives.
>
> B. With Remediation: The student is required to take a retest. The student has not met training objectives and must successfully pass retest prior to completion of division.
>
> 2. <u>Setback</u>: The student receives an extension of training with remediation. The student will repeat all or part of the current division or previous division curriculum as recommended by the ARB. Students will normally be setback only to repeat the training objectives that have not been satisfactorily demonstrated. If repeating additional training objectives that precede the failed training objective is a remediation method that will benefit the student, the ARB may recommend it.
>
> 3. <u>Drop from Training</u>: A student has not met training objectives and should be permanently removed from training. When the ARB recommends a drop from training the student must demonstrate unwillingness or inability to continue the training.

The ARB process is time-consuming, costly, and labor-intensive since it involves many players. Because of this, setbacks are granted only after all types of remediation are exhausted. The following people have authority and responsibility in the process in accordance with NAVSCOLEODINST 5420.1U:

1. Testing Officer. Ensure that the student is tested in accordance with instruction.

2. Instructor. Ensure NAVSCOLEOD Form 1610/1 Sections I through VII are completed properly. Once all information is correctly filled out the package will be forwarded to the Division Officer for action.

3. Division Officer. Ensure the student is counseled on his or her failure; fills out NAVSCOLEOD Form 1610/1, check previous sections for correctness and forward to the training officer for action.

4. Training Officer. Conduct student interview and review student's academic history. For a student's initial setback, the Training Officer (TO) will determine if the student meets the requirement for an academic setback or drop from training per instruction. For all other setbacks, an ARB will be convened. The Training Officer will ensure ARB packages are complete, deviation notice updated, and students are present prior to ARB convening in proper uniform. The Training Officer will work with CISO to ensure board composition is in compliance with instruction, based on service component.

5. ARB Board Chairman. Ensure boards are conducted per instruction. The student record with disposition recommendation will be forwarded to the Commanding Officer (CO) or Executive Officer (XO) by the Training Officer and via the Service Detachment Commander. The Executive Officer will retain final decision for ARB recommendations, which are agreed to by the Service Detachment Commander. All others will be forwarded to the Commanding Officer for final decision. In these cases, the Service Detachment Commander or his designated representative may present the board package to the CO. The Training Officer will take necessary action to effect the student's disposition. If the student is dropped from training, he or she shall be turned over to the Training Support Officer or Service Detachment Commander. The second and all subsequent ARBs will consist of a chairman and at least two additional service members who shall be certified instructors.

6. Detachment Commanders. Service Detachment Commanders and/or Liaison Officers will be notified by the Training Department of all impending boards. Commanders will review the ARB package and make recommendations to the Commanding Officer.

> 7. <u>Commanding Officer</u>. Review all completed ARB packages and exercise final disposition authority in all cases unless the Service Commander disagrees with the ARBs recommendation. (NAVSCOLEOD, 2008)

NAVSCHOLEODINST 5420.1U also states:

> Setbacks are categorized as Academic or Non-Academic depending on the circumstances. Non-academic setbacks may occur when the student is unable to complete training due to illness or special circumstances outside the control of the course or the student. Academic setbacks occur after the failure of the first retest. The Training Officer as a result of unsuccessful remediation and retesting may grant initial academic setbacks. Remediation efforts may include supplemental examinations by the Division Officer with approval of the Training Officer. Supplemental examination will only be given if an administered test is deemed invalid due to technical information or instructor error. The Training Officer will inform CISO when a supplemental test is directed. CISO will take appropriate action per NAVSCOLEOD instructions. If remediation can be achieved in any way other than setback, it shall be considered first. Students will be setback only when the training objectives have not been satisfactorily demonstrated. (NAVSCOLEOD, 2008)

The increase in the number of students at NAVSCOLEOD has, in turn, caused an increase in ARBs. As there are no set faculty members employed solely to conduct review boards, faculty are pulled from their primary jobs to sit as board members. Moreover, the numerous responsibilities of each person in the ARB process reveal the lengthy, time consuming, paper-work intensive procedure. An academic review board is comprised of six people: one chairman, four service representatives and the student himself or herself. A second ARB is comprised of an additional two board members. Each review board lasts a minimum of 30 minutes, not including the hours of paperwork and counseling that instructors and staff complete beforehand.

In the six months from October 2008 until March 2009, 306 students were subject to an ARB. Had the Training Officer setback not been implemented (see section II), those 306 review boards would have required at least 918 man hours to handle this process (306 boards x 6 people/board x 30 min/board). This number further breaks down into 765 hours lost to instructors and 153 hours lost to students. Instructors, therefore, lost over 95 days to review boards in the last six months (765 hours / 8-hours/day = 95.635 days) and students lost 19 days to review boards in the last six months (153 hours / 8 hours/day= 19.125 days).

In addition, these days represent value forgone to the military as teachers are not instructing and students are not learning. The average board member is an E-7 or above and the student an E-5 or below. The average E-7 earns $245.24/day and the average E-5 earns $169.98/day (see Exhibit 2, FY 10 Projected Individual Programming Rates). A simplified calculation using these numbers suggests an estimate of $27,000 lost to conducting academic review boards over the last six months. (The days lost to review boards can be converted into $23,298.80 cost to instructors (95 days x $245.24/day) and $3,229 cost to students (19 days x $169.98), totaling $26,528.24 dollars). This amount only takes into account the review board itself, not the hours spent on counseling, paperwork and remediation; those costs are too variable to estimate for the purposes of this paper. In addition, the time students wait to return to training is also a cost lost to the military. It is clear that this lost time and money will continue to accumulate as student population increases at the schoolhouse, presuming a stable attrition rate.

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II. NAVSCOLEOD INSTRUCTION 5420.1U REVIEW

Due to the high number of students awaiting academic review boards, NAVSCOLEOD has developed the process of a Training Officer (TO) setback. This process strives to minimize time lost to instructors and students by utilizing an interview process and a graduation prediction model in lieu of an ARB to determine if a student should be set back or dropped from training upon the failure of his or her first retest. The model identifies students who are more likely to complete training upon their initial setback based on historical data. If the student fails a test and a retest after his or her first setback, a full ARB must be convened.

This model is currently in use, but the data is outdated. This MBA project updates the model with current data from NAVSCOLEOD. The Academic Review Board instruction 5420.1U describes the process of the Training Officer Setback:

> The decision tool will improve training efficiency without compromising standards. The decision tool uses GPA and the first setback area to predict graduation. The tool predicts successful completion of training for 95% of graduates who experienced a setback, and the tool is far more accurate overall than the traditional ARB process.
>
> The tool has an additional value in that changing the decision threshold allows it to predict nearly 100% of graduates while keeping false alarms in check. This decisional feature enables the tool to respond to forward demand signals more efficiently than the traditional ARB process.
>
> <u>Process</u>. The student’s first Academic Review Board/Training Officer Setback will consist of reporting to the Training Office in proper service dress uniform. The TO, Assistant Training Officer or Training Leading Chief Petty Officer will interview the student. The justification to remove from or continue with training may be based upon the student’s grade point average and division recommendation where the student would be set back in. If the student is not at or below the minimum allowed GPA for the specific division the training office may grant a TO setback if warranted. The student will be recommended for drop if the GPA is less than that determined by the graduation prediction model. (NAVSCOLEOD, 2008)

This process virtually eliminates the need for an Academic Review Board for those students whose GPA is above the historical average, indicating that those student have a high probability of completing training and graduating from EOD school. If a student's average is below the allowed GPA, he or she will be dropped from training as the model predicts it is highly unlikely this student will graduate. The instruction further states:

> Statistical Model. The model will only be used for the area of the first setback to help determine if a student has the ability to complete NAVSCOLEOD objectives, and will not be used to address any further academic failures.
>
> Annual Statistical Certification. The statistical data used in lieu of the first ARB will be checked on an annual basis using the first class convening in the new fiscal year. This class will be used to ensure the statistical method is still valid. Every student within the class will be given an ARB vise using the model for first setback situations. Each student that is given an ARB will be compared to the model. Using the table below, the model non-graduate predictions should not differ by more than the number in the right hand column.
>
> Table 1. Missed Students Based on Sample Size
>
> | Class Sample Size (Number of Students) | Students that Graduate and Model Predicted Would Not |
> |---|---|
> | 12–20 | 4 |
> | 21–24 | 5 |
> | 35–44 | 6 |
>
> The Training Officer will be responsible for maintaining statistical validation data for this model. Additionally, the Training Officer will coordinate periodic Technical Training Acceptance Board review of the ARB instruction and the annual statistical validation results to ensure the process is producing desired results. Subsequent failure of retests will result in an ARB. (NAVSCOLEOD, 2008)

The Human Performance Center Detachment at the Center for Explosive Ordnance Disposal and Diving provided a preliminary assessment of the model to determine if the model satisfied Chapter 3 Section 6 NAVEDTRA 135 B. Two statements were identified that may call into question the use of the ARB decision tool:

> 1. Students enrolled in Class “A” and “C” schools will be academically dropped from training only as a result of an ARB recommendation (p. 3-6-1).

A Class “A” School provides basic technical knowledge and skills required for a rating and further specialized training. A Class “C” School provides advanced knowledge, skills and techniques to perform a particular job in a billet (The Naval Education and Training Command, 2009).

> 2. Administrative procedures that result in “automatic” drops or setback are not authorized (p. 3-6-2) (Swiergosz, Aaberg, & West, 2005).

The Performance Center determined that these factors are mitigated by the following.

1. NAVEDTRA 135 does not dictate how an ARB decision will be made

2. The use of a decision tool does not preclude normal chain-of-command routing for CO approval

3. The decision tool is an unbiased recommendation

4. The decision tool is a better overall predictor of graduation outcomes than the traditional ARB process

5. Decision tool output will be forwarded to the International Military Student Manager when an international military student is under review (Swiergosz, Aaberg, & West, 2005)

The Performance Center also amplified:

> NAVSCOLEOD collected data over a two-year period from FY04–FY05 to develop the decision tool that predicts successful completion of training. These efforts produced the following regression equation:
>
> $$\text{Graduation} = -4.585 + 0.057 \times \text{GPA} + 0.032 \times \text{Setback Area}$$
>
> where -4.585 is the y-intercept (the point at which the regression line crosses the y-axis), 0.057 is the coefficient for GPA and 0.032 is the coefficient for setback area (variable that represents the first test failure area). Expected outcome probabilities are show in Table 1 when the threshold for predicting graduation (no-yes; 0–1) is set at 0.5.

As shown in Table 1, the ARB decision tool is a robust predictor of graduation (95%); less than 5 % of students who actually graduate will be "missed." It is also evident from Table 1 that the student receives a "benefit of the doubt" from the decision tool in that, successful completion of training is predicted 27% of the time when a student will actually fail (false-alarm).

To clarify, once a setback student graduates or fails, the school looks back at whether or not his or her model score was above the decision threshold.

The decision threshold can be set to achieve different outcome probabilities. For example, setting the decision threshold at 0.4 is expected to predict nearly all occurrences of graduation and elevate the false-alarm rate from 27% to 66%.

Table 2. ARB Model Probability Matrix

	Graduation	
Model Prediction	Yes	No
Yes	.95	.27
No	.05	.73

*FY04-05 data (n = 1166). Decision threshold = 0.5.

The outcome distributions in Table 2 represent data collected during FY05 validation. These outcomes parallel the expected probabilities in Table 1.

Table 3. FY05 ARB Model Validation

	Graduation	
Model Prediction	Yes	No
Yes	208 (97%)	15 (29%)
No	7 (3%)	36 (71%)

*Standard decision threshold = 0.5. Data are from a different sample (n = 266) than data used to derive the model (regression equation, p. 2; Table 1). Actual counts are shown with graduation outcome percentages in parentheses.

The outcome distributions in Table 3 represent data collected during FY05 validation when the decision threshold was set at 0.4. The "hit" rate is parallel to the expected probabilities (100%) and the false alarm rate was significantly lower (49%) than the expected (66%) $x^2(1) = 6.38, p < .01$.

Table 4. FY05 ARB Model Validation with a more Liberal Decision Threshold

Model Prediction	Graduation Yes	Graduation No
Yes	215 (100%)	25 (49%)
No	0 (0%)	26 (51%)

*Decision threshold = 0.4. Data is from the same sample (n = 266) used to validate the 0.5 decision threshold (Table 2). Actual counts are shown with percentages in parentheses.

The Performance Center expressed the additional concerns that:

1. Stakeholders must determine what constitutes a significant deviation from the expected model probabilities listed in Table 2.

2. The only decision thresholds that appear to be useful are 0.5 (default) and 0.4 as previously mentioned. Setting the decision tool at 0.4 is expected to yield higher "hit" (100%) and false alarm rates (50%). Force demand signals and the cost of false alarms will presumably dictate the decision threshold over a designated time period.

The goals of this decision tool were to reduce man-hours associated with the ARB process, avoid training costs associated with academic failures and enhance the ability to meet force demand signals (Swiergosz, Aaberg, & West, 2005). This model is currently used on a regular basis at EOD School; in the last six months, for the 306 students awaiting ARBs, the Training Officer used the model 277 times, while only convening 29 actual review boards. The time savings to instructors and students from this process is approximately 831 man hours semi-annually (918 man hours for 306 boards minus 87 man hours for 29 boards). However, the statistical GPA that the model is based on reflects old data from 2004 and 2005. This project uses current student performance data (GPA) inserted into the regression equation currently used to predict Graduation.

$$\text{Graduation Score} = -4.585 + 0.057 \times \text{GPA} + 0.032 \times \text{Setback Area}$$

The next section discusses past research conducted on the study of Explosive Ordnance Disposal Training.

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III. LITERATURE REVIEW

Edwin Bundy, Roderick Sims, Stephen Briggs and Joyce and Robert Hogan have conducted additional research on cognitive and non-cognitive predictors of success in Explosive Ordnance Disposal training over the past 30 years. All these individuals strived to predict accurately which students would be successful in EOD training. If military detailers could recruit the "correct" candidate, attrition rates would decrease, manning in the community would increase, and the military would receive maximum return on investment as fewer resources are spent on non-graduates.

Bundy and Sims from the Technical Support Working Group, Explosives Detection Subgroup, conducted a study called *Commonalities in an uncommon profession: Bomb disposal*. The study discusses the importance of having highly trained, responsive and consistent bomb disposal technicians in both the military and private sector. The purpose of the article itself is to identify if specific learning styles and intelligence strengths are common among professionals in this field through the administration of analytical tests. The results can be used as a predictor of success in bomb disposal training by identifying similar character traits that are inherent in successful EOD technicians.

Their study sought to identify what cognitive characteristics make a "good" EOD technician. More specifically, the purpose was to "investigate the extent to which individual learner preferences, as measured by learning styles and multiple intelligences, impact the effectiveness of bomb disposal training" (Bundy, 2007). Bundy determined that learning style preferences and intelligence strengths could be used as predictors for academic success because EOD technicians tend to share common traits. Bundy and Sims identified these commonalities through the Canfield Learning Styles Inventory (LSI) and Multiple Intelligences Developmental Assessment Scales (MIDAS). The caveat to his claim is that other variables must be considered because this research did not address the psychological and neuropsychological characteristics of EOD technicians.

The author sampled a wide demographic of EOD technicians, both civilian and military and determined that commonalities existed despite race, age, gender, education, and military affiliation. Bundy determined bomb technicians preferred specific learning styles while showing aversion to others. In addition, EOD technicians shared similar strengths and weaknesses in certain types of intelligence. The author's goal is to use this information to alter the training and education curriculum for EOD technicians to be exploit these characteristics and to anticipate and accommodate their learning capabilities. Identification of common strengths and weakness among bomb disposal technicians is important knowledge for instructors. This will allow them to tailor training to address problems that may incur in the field. In addition, this data can inform the EOD selection process to select the proper candidate for EOD training more accurately.

Bomb technicians shared similar results on the LSI and MIDAS tests. Results from the LSI showed strong commonalities in the three areas of the test (Bundy, 2007).

1. Conditions for Learning: over 75% of bomb technicians sampled showed high preference for the following.
    - *Detail*: requiring specific information on assignments, requirements and rules
    - *Authority*: desiring classroom discipline and maintenance of order
    - *Organizational*: wanting course work to be logically and clearly organized with meaningful assignments and sequence of activities
    - *Competition*: desiring comparison with others; needing to know how one is doing in relation to others
2. Expectation-for-Course-Grade: 72% reported a high Expectation-for-Course-Grade.
3. Learner Typology: technicians had preferences common to the *Social/Applied* and *Independent/Applied* categories. The categories are similar in that all prefer opportunities to work in situations that approximate real-world environments while *Social* learners seek work with others and *Independents* prefer to work alone in a self-selected path toward a goal.

Dr. Shearer, developer of the MIDAS test, reported that results from the bomb technicians were unusual (Bundy, 2007). Technicians consistently rated themselves lower in certain areas as compared with other segments of the population, but results were uniformly consistent within the sample itself. Most technicians rated themselves strong on the following.

1. Interpersonal Intelligence (44%): the potential for working with others, as used in understanding people, leading and organizing others, communicating and resolving conflicts.
2. Intrapersonal Intelligence (42%): the potential for understanding ourselves as used in recognizing one's own strengths and weaknesses and setting personal goals.

EOD technicians, however, scored themselves extremely low on the following.

3. Musical Intelligence (24%): the potential for thinking in music; for hearing, recognizing and remembering patterns as used in singing, identifying sounds and remembering melodies and rhythms.

Comparison of the two tests showed that a high score on the *Intrapersonal* scale of the LSI correlated with the high *Expectation-for-Course-Grade* on the MIDAS test (Bundy, 2007). Translated, this means a person with a high degree of self-efficacy, or self-worth, would have high expectations of receiving a good grade. Since each of these areas was ranked highest by the majority of bomb technicians, this is perhaps an indicator of potential success for future bomb technicians (Bundy, 2007).

Bundy and Sims agreed that bomb disposal is inherently dangerous and the EOD community seeks to attract, train, and retain individuals who are physically, mentally and emotionally capable of performing the diverse and complex tasks required of bomb disposal technicians (Bundy, 2007). They further acknowledge that the EOD community is continually understaffed in part due to the attrition rate during initial training. Their research identified common characteristics among bomb disposal technicians. This data can be used to distinguish mismatches between learning style preference or intelligence strengths of an EOD candidate and those EOD technicians that have been successful in the field.

This research is useful in pre-selecting EOD candidates, especially when used in conjunction with the ASVAB and physical fitness test. In reference to this project, perhaps it can be incorporated into the ARB's decision of whether or not to keep a student in training. If the student displays the common learning style preferences and intelligence strengths shared by successful EOD technicians, he or she may be more likely to graduate than a student who does not possess the similar characteristics.

Hogan, Hogan and Briggs (1984) wrote a study titled *Psychological and Physical Performance Factors Associated with Attrition in Explosive Ordnance Disposal Training*. The Naval Medical Research and Development Command supported their research. They conducted three studies designed to predict performance in EOD training. The research team followed a sample of students in all different phases of EOD training, some in the beginning, some in the middle and still others close to graduation. Like Bundy, the team wanted to develop valid measures to identify qualified candidates and reduce attrition created by recruiting inappropriate personnel. The first study investigates psychological factors underlying successful completion of the EOD School. The second study identifies physical performance predictors of success in preconditioning training program. The third study investigates both psychological and physical factors associated with completion of a twelve-week second-class diver course. The goal was to develop a comprehensive set of selection procedures and recommendations for recruiting potential EOD candidates (Hogan, Hogan, & Briggs, 1984).

The first study investigated non-cognitive measures of a sample of EOD technicians currently undergoing training at EOD School. Students were given four tests.

1. CPI (California Psychological Inventory)—the most fully validated measure of normal personality
2. HPI (Hogan Personality Inventory)—assesses six factors associated with status and popularity in everyday life: Intelligence, Adjustment, Prudence, Ambition, Sociability and Likeability
3. SDS (Self Directed Search)—the standard vocational preference battery
4. ASVAB (Armed Service Vocational Aptitude Battery)—the primary cognitive battery used in the Armed Services

The results of the multiple tests revealed EOD technicians were realistic, investigative, intellectual, self assured and had social interests. These characteristics paralleled the profiles of athletes, engineers, pilots or technicians. People who deviate from this profile, such as artists or musicians may not be successful in EOD training and will be at a high risk for attrition. However, candidates possessing these traits will more likely to successfully complete the rigors of EOD training (Hogan, Hogan, & Briggs, 1984).

The research team also determined that the use of vocational preference and non-cognitive measures are highly reliable predictors of academic success at EOD School. The team also found that the ASVAB was of little utility and highly inaccurate in selecting candidates who would ultimately graduate from EOD training (Hogan, Hogan, & Briggs, 1984).

In their second study, Hogan et al. analyzed the physical aspect of Navy EOD training. In 1982, pre-conditioning training and dive school accounted for 70% of the total attritions in the entire Navy EOD training pipeline (Hogan, Hogan, & Briggs, 1984). In 2008, pre-conditioning training accounted for 50% of attrition, dive training accounted for 20% of attrition and EOD School for 30% of Navy attrition (Getman, 2009). Hogan, et al. identified seven dimensions that provide a complete coverage of physical strengths needed for job performance in any demanding field: Muscular Strength, Muscular Power, Muscular Endurance, Cardiovascular Endurance, Flexibility, Balance, and Neuromuscular Coordination.

The results of the physical study found that extensive array of measures are necessary to predict performance in complex training programs. The researchers had to administer 26 different physical tests to lead to accurate prediction of successful dive training. They found that of the seven dimensions, that muscular strength was not a predictor of performance. Similarly, height, weight and body fat were not accurate predictors either. These findings suggest that successful performance in an arduous physical job is not related to physical size or strength. The best predictor, they determined was cardiovascular endurance (Hogan, Hogan, & Briggs, 1984).

Their final study combined multiple elements, such as psychological, cognitive, physical and manual dexterity to predict successful completion of dive training. They found that attrition in dive training is due to a specific set of factors. Students do not tend to fail due lack of cognitive competency; they did not typically attrite for academic reasons. Instead, personal and physical factors were the primary reasons for training failures. The psychological tests determined that students who were successful in dive training were well-adjusted, self-confident and mature, as well as hard working and achievement oriented. Those who were not successful were categorized as immature, anxious and self-doubting. The physical tests most predictive of successful performance were cardiovascular and muscular endurance. Therefore, candidates must be able to persist in physical activity while withstanding fatigue to graduate from dive training (Hogan, Hogan, & Briggs, 1984).

Overall Hogan, Hogan and Briggs indentified predictors for success during the academic portion of EOD School. They have also determined who will fail out of pre-conditioning training and who is at risk to attrite during dive training. By testing EOD candidates with the SDS and HPI and incorporating cardiovascular endurance runs into the screening process, program managers can significantly reduce attrition in the EOD community (Hogan, Hogan, & Briggs, 1984).

The extensive research done in this field dating from 1982 indicates that EOD attrition is high. However, the problem lies not in the demanding and arduous EOD training curriculum, but in the candidates selected for training. There exists a percentage of the population who are not cut out for the highly stressful, physically demanding and mentally challenging job of bomb disposal. Those people must be weeded out of the process. However, if recruiters can use the research findings that successful EOD technicians share similar traits while tweaking the screening process to include specific psychological and physical factors to select the appropriate candidates from the beginning, standards in the community would not suffer, manning would increase and the military would experience cost savings.

IV. METHODOLOGY

Data was collected from EOD School on all student records from 1999 until 2009 in order to answer the research question "Is the graduation prediction model still valid?" Of the students who experienced at least one academic setback, we calculated their "model score" by imputing their unadjusted performance data (GPA) and their setback area in training, into the regression equation:

$$\text{Graduation Score} = -4.585 + 0.057 \times \text{GPA} + 0.032 \times \text{Setback Area}$$

As stated before, −4.585 is the y-intercept (the point at which the regression line crosses the y-axis), 0.057 is the coefficient for GPA and 0.032 is the coefficient for setback area. The setback area is a number from 1 to 12 that corresponds with the particular division in which the student failed two consecutive tests and was consequently removed from training.

From years 2004–2008, the result from this equation produced a number ranging from −.848 to 1.29, which we labeled "Model Score." NAVSCOLEODINST 5420.1U says, "The tool predicts successful completion of training for 95% of graduates who experienced a setback." To clarify, of all the students who graduate and had experienced a training setback, 95% had had a model score of .5 or higher and therefore, the model predicted correctly that he or she would graduate. On the other hand, only 5% of students who graduated and who had experienced a training setback had had a model score below .5, so that the model predicted incorrectly that they would not graduate. When the threshold is lowered, more students will be "captured" and fewer graduates will be "missed" by the model. For example, under the reduced threshold of .4 used in FY05, all graduates with setbacks had model scores, at the time of setback, exceeding the threshold. Translated, no student who graduated would have been mistakenly dropped from training.

This is only one way to interpret the data; we will also be analyzing the same data with a different perspective. The school's instruction first asks, "Did the student graduate?" and then looks back to find out what the model predicted. We also want to look at the data with the perspective of predicting the student’s future at the point of his or her setback. At the point of the setback, we want to know what the model predicted and then compare it to the end result (graduated or not graduated). This will allow us to determine how accurately the model can predict the end result of graduation or failure. These two perspectives will be discussed in greater detail.

V. DATA VALIDATION

Our first step was to ensure the data we collected was representative of the data used to build the regression equation in the first place. In order to do this, we had to filter the data from the unabridged data set. Since the school's regression equation was built using calendar years 2004 and 2005, we focused only on the students who experienced a setback during those years. We also filtered out non-academic drops and setbacks for other than academic reasons, such as medical, administrative, behavioral or security issues. With this filtered set, there were now only two reasons for a student's termination, graduation or an academic removal from training. Students who never experienced a training setback were also filtered out. A model score cannot be calculated for these students, as there is no "Setback Area" to be factored into the equation.

During the analysis of our data set, we noticed some issues that were cause for concern. These issues included discrepancies in the labeling of the data, as well as contradictory pieces of information within individual student records. A significant mislabeling that we noticed was between the "Termination Reason" and "Graduation Status." We found numerous students who were listed as graduated from the school but were apparently terminated due to academic and non-academic reasons. In addition, we found students who were listed as terminated due to graduation yet their graduation status was shown as "Not Graduating." These conflicts made it difficult to determine the actual number of students who graduated. Before we generated our results, we had to decide what the "better" entry was and calculate our data based on that decision. We recommend that EOD School be precise in its data entries, in order to ensure accurate research.

With the data we data we had, the filtered set for calendar years 2004 and 2005 resulted in a sample size of n = 627.

We examined four sets of students within that sample.

1. The students that the model predicted *would* graduate because they had a model score greater than .5 and *did* in fact graduate (366)
2. The students the model predicted *would* graduate because they had a model score greater than .5 but *did not* graduate (132)

3. The students the model predicted *would not* graduate because they had a model score less than .5 and actually *did not* graduate (89)

4. The students that the model predicted *would not* graduate because they had a model score less than .5 but actually *did* graduate (40)

These numbers are presented in Table 5.

Table 5. 2004–2005 Student Setback Data (Threshold = .5)

Prediction	Graduated: Yes	No	Total
Yes	366	132	498
No	40	89	129
Total	406	221	627

Converting this data into percentages produces the table below.

Table 6. 2004–2005 Predictions Compared to Graduation Results

Prediction	Graduated: Yes	No
Yes	90.10%	59.70%
No	9.90%	40.30%
Total	100.00%	100.00%

Table 6 reveals that using the data we collected, 90.1% of all the students who graduated and experienced a training setback had had a model score of .5 or higher at the time of setback, so that the model predicted correctly they would graduate. Only 9.9% of students who graduated and experienced a training setback had had a model score below .5, the model predicting *incorrectly* that they *would not* graduate. Simply stated, 9.9% of all students who graduated and experienced a setback had been predicted to fail by the model.

In addition, Table 6 shows that once a student experienced a training setback, the model would err on the side of caution and give students the "benefit of the doubt." Of the students who *did not* graduate and experienced a setback, 59.7% had had a model score greater than .5, so that the model predicted they *would* graduate. This represents a cost lost to the military as the model retained students who would eventually fail.

We compared this data to the ARB Model Probability Matrix found in NAVSCOLEODINST 5420.1U and referenced in Table 2. The model currently in use at NAVSCOLEOD claims that 95% of graduates who experienced a setback would have had model scores exceeding .5, while only 5% would have had scores below that threshold. Our results of 90.1% and 9.9% do not meet criteria specified within the instruction. This variation may be due to a difference in sample sizes. Our sample size of 627 was not the same as the school's sample size of 1166 due to differences in data filtering.

When the model was developed, the sample size of 1,166 included all students from FY2004–2005, even those who never experienced a training setback. However, we filtered out students who never experienced a training setback, as there is no "setback area" to be factored into the regression equation. These students would not be able to tell us if the model predicted correctly or incorrectly since they were never subject to the model in the first place.

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VI. DATA ANALYSIS

Based on the data EOD School provided, we concluded our data set was slightly different from the data used in the school's instruction, as referenced in differences in sample sizes. However, we will use the data that was provided to continue our analysis. The first and most important point of this paper is to present two different ways to analyze this data, the forward-looking analysis and the backward-looking analysis.

The analysis in NAVSCOLEODINST 5420.1U takes a backward-looking approach in which the outcome is already known (i.e., a student graduates or does not graduate). We will use the data in Table 5 and the corresponding percentages in Table 6 to represent this approach in Figure 1.

Figure 1 illustrates the setup to this analysis.

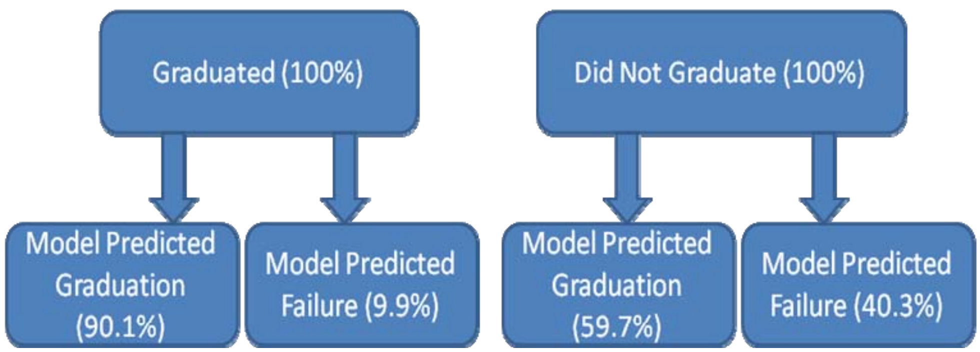

Figure 1. Backward-Looking Analysis

Knowing the outcome, students are divided into two groups-those who graduated and those who did not. Once the groups are divided, the model focuses on each group and looks back at what their corresponding model scores were at the time of setback. In the graduation group, 90.1% of students had model scores greater than .5, so these students' outcomes would have been correctly predicted at the time of the setback. Simply put, the model correctly identified 90.1% of the graduates. Among graduates, 9.9% had scores smaller than .5. Simply put, the model gave low scores to 9.9% of the graduates.

Among non-graduates, 59.7% had model scores above .5. Simply, the model cautiously kept 59.7% of students who would eventually fail out. Although this number may seem alarmingly high, it offers the student the "benefit of the doubt" by allowing him or her to continue training. Finally, among non-graduates, 40.3% had model scores below .5. The model correctly identified 40.3% of eventual non-graduates.

The forward-looking analysis allows us to examine the prediction success of the model without knowing the outcome in advance. It shows that once you make a prediction, you can determine the probability of getting the prediction correct. Table 7 provides another viewpoint of the data in Table 5.

Table 7. 2004–2005 Forward-Looking Analysis

	Graduated		
Prediction	Yes	No	Total
Yes	73.50%	26.50%	100.00%
No	31.00%	69.00%	100.00%

Figure 2 further illustrates the setup to this analysis.

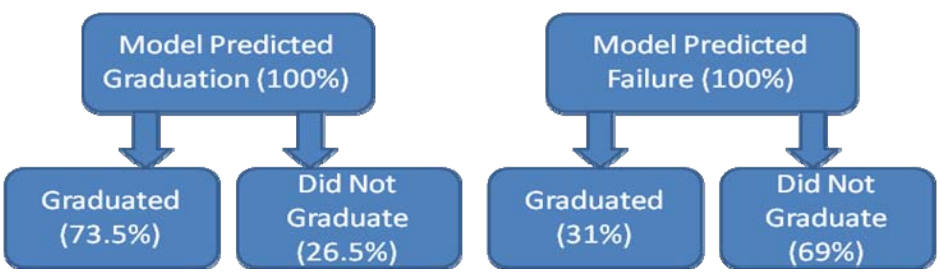

Figure 2. Forward-Looking Analysis

This approach is a more logical progression as the setback occurs first, followed by the outcome of graduated or not graduated. For example, in calendar years 2004 and 2005, 129 students were predicted to fail EOD school. However, 40 of those students (31%) went on to graduate. Conversely, 89 of those 129 students (69%) failed as predicted. Of the 498 students who the model predicted to graduate, 132 (26.5%) would have failed, while 366 (73.5%) would have been predicted correctly. As the School's instruction states, inaccuracy is more acceptable when the model predicts a graduation and the student fails.

While the data used to generate the percentages in the backward-looking analysis and the forward-looking analysis is the same, the viewpoints are different. Although the graduation prediction model currently in use at EOD School is based on the backward-looking approach, we claim that the forward-looking approach is a more logical way to analyze the data.

The main differences in analyzing the data in Table 5 from years 2004 and 2005 are listed below. We use the shortened term "setbacks" to identify students who experienced an academic training setback.

1. Correctly Predicting Graduation
   The Forward-Looking Analysis correctly predicts graduation in 73.5% of setbacks who had a model score of .5 or above.

   The Backward-Looking Analysis noted a model score of .5 or above in 90.1% of those who graduated.

2. Incorrectly Predicating Graduation (False-Alarm)
   The Forward-Looking Analysis falsely predicts graduation in 26.5% of setbacks who had a model score of .5 or above.

   The Backward-Looking Analysis noted a model score of .5 or above in 59.7% of those who did not graduate.

3. Correctly Predicting Failures (Non-Graduates)
   The Forward-Looking Approach correctly predicts failure in 69% of setbacks who had a model score of less than .5.

   The Backward-Looking Approach noted a model score of less than .5 in 40.3% of those who did not graduate.

4. Incorrectly Predicting Failures (Would-be Graduates)
   The Forward-Looking Approach falsely predicts failure in 31% of those who had a model score less than .5.

   The Backward-Looking Approach noted a model score of less than .5 in 9.9% of those who did graduate.

The last item is perhaps the most important difference between the two approaches. These two viewpoints present the different levels of error in the graduation prediction model. The forward-looking approach shows of all students the model predicts *will not* graduate, 31% of those students actually *will* graduate. On the other hand, the backward-looking approach shows of all students who graduated, 9.9% were predicted to fail. The model would have dropped these students from training, but given the opportunity they would go on to graduate and become EOD technicians. The backward-looking analysis claims to “miss” a much smaller number of students (9.9%) then the forward-looking analysis (31%). It is important for NAVSCOLEOD to recognize this difference. By using the backward-looking approach, they believe their margin of error is small, while the forward-looking approach shows a much larger error rate.

VII. MODEL VALIDATION

We have validated our data set and determined that our data is slightly different than the data used to construct the graduation prediction model. We have also discussed the two different approaches to analyze the data in this research. Now we can move on to answereing the research question, “Is the model still valid?”

We extracted the data (GPA) from students who experienced an academic training setback in years 2004–2008 to determine if the tool is still an accurate predictor of graduation. We filtered out students in years 2009, as they have not yet completed training. Again, we included only students who terminated their training for one of two reasons, graduation or an academic removal from training. Non-academic drops and setbacks for reasons, such as medical, administrative, behavioral or security were filtered out of our data set. Students who never experienced a training setback were also filtered out, as these students were never assigned a model score (since there was no setback area to be factored into the regression equation). Finally, we removed students that we determined were dropped because they had low model scores since these students never had the opportunity to continue and graduate. The filtered data resulted in a sample size of $n = 1495$.

Using a pivot table, we examined each student’s model score against a “Yes” or “No” indicating actual graduation. Model scores from our sample ranged from −.848 to 1.29 and the model used a threshold of .5 and higher as the predictor of graduation. Said a different way, if a student had a model score of .5 or greater the model would predict that he or she would graduate and therefore it would retain them in training. If a student had a model score below .5, the model would predict that he or she would not graduate and recommend that he or she be dropped from training. Our data produced Table 8.

Table 8. 2004–2008 Student Setback Data (Threshold =.5)

Prediction	Graduated Yes	Graduated No	Total
Yes	927	386	1,313
No	58	124	182
Total	985	510	1,495

As we did on Table 6, we focused the data into two groups (Graduated or Did Not Graduate) and computed the percentages of whether the model predicted graduation or failure. Using the backward-looking analysis, this data resulted in the following table:

Table 9. 2004–2008 Backward-Looking Analysis

Prediction	Graduated Yes	Graduated No
Yes	94.10%	75.70%
No	5.90%	24.30%
Total	100.00%	100.00%

Comparing the results from Table 9 to Table 6, we see that the numbers have changed only slightly over the years. In 2004–2005, of all the students who graduated, the model predicted failure in 9.9% of those setback cases. Validating the model with current data (2004–2008) revealed that of all the students who graduated, only 5.9% were predicted to fail. These two numbers (5.9% and 9.9%) are similar, but proves the model has gotten more accurate over the years in predicting success among graduates. This 5.9% is actually closer to the 5% threshold specified in NAVSCOLEODINST 5420.1U than the earlier number.

In the years 2004–2005, of all students who failed, the model predicted that 59.7% would graduate. Validating the model with current data (2004–2008) revealed that of all the students who failed, the model predicted 75.7% would graduate. These two numbers (59.7% and 75.7%) are not close in range, and proves the model has become more inaccurate over the years concerning this measure. It has allowed more students who have a low probability of ever graduating to remain in training. This number represents a cost to the military as there is no return on investment on students who do not graduate.

In addition, the updated model accurately predicted the future of 94.1% of graduates and 24.3% of non-graduates (compared to 90.1% and 40.3% in 2004–2005). The model has gotten more accurate over the years in predicting graduates, but less accurate in predicting non-graduates.

Using the forward-looking analysis for the same data gathered in years 2004 through 2008, the following table was generated.

Table 10. 2004–2008 Forward-Looking Analysis

	Graduated		
Prediction	Yes	No	Total
Yes	70.60%	29.40%	100.00%
No	31.90%	68.10%	100.00%

Comparing the results from Table 10 to Table 7, we see that the numbers have changed only slightly. In the years 2004–2005, among students who experienced an academic setback, 31.9% of those predicted to not graduate by the model did, in fact, graduate. These students would have been dropped from training by the model, however given the opportunity to continue, they went go on to graduate. Validating the model with current data (2004–2008) revealed that 31.9% of students who were predicted to fail by the model actually went on to graduate. These two numbers (31% and 31.9%) are very similar.

Validating the model with current data (2004–2008) revealed that 29.4% of students predicted by the model to graduate actually failed out. This number is similar to the 26.5% observed in years 2004–2005.

In addition, the updated model using the forward-looking approach accurately predicted the graduation in 70.6% of those with high model scores and 68.1% of those predicted to fail actually failed (compared with similar numbers of 73.5% and 69% in years 2004–2005).

Overall, without regard to a specific analysis, the updated model accurately predicted the future of 70.3% of setback cases (1,051 out of 1,495 students) compared to 72.6% (455 out of 627 students) in years 2004–2005. Again, these numbers are similar, but show that the model has dropped slightly in accuracy over the years.

VIII. LOWERING THE THRESHOLD

When the threshold is lowered to .4 (applying the same filters), our data produced Table 11, with corresponding percentages in Tables 12 and 13, is produced.

Table 11. 2004–2008 Student Setback Data (Threshold = .4)

	Graduated		
Prediction	Yes	No	Total
Yes	957	429	1,386
No	28	81	109
Total	985	510	1,495

Table 12. 2004–2008 Backward-Looking Analysis

	Graduated	
Prediction	Yes	No
Yes	97.20%	84.10%
No	2.80%	15.90%
Total	100.00%	100.00%

Table 13. 2004–2008 Forward-Looking Analysis

	Graduated		
Prediction	Yes	No	Total
Yes	69.0%	31.0%	100.00%
No	25.7%	74.3%	100.00%

If the threshold is lowered to .4, Table 12 shows the model currently in use at NAVSCOLEOD (backward-looking analysis) became more accurate (97.2% compared to 94.1% at the .5 threshold).

Table 13 (forward-looking analysis) shows that the model correctly predicted graduation 69% of the time (that is, 69% of students with model scores above .4 ended up graduating), compared to 70.6% at the .5 threshold.

The benefit of lowering the threshold in both the forward- and backward-looking analysis is an increase in overall prediction success. As seen above, the probability of dropping a student who will eventually graduate is lowered.

The trade-off of decreasing the threshold is an increase in the false-alarm rate. In both approaches, by lowering the threshold the model will keep students who will ultimately never graduate. This represents a cost lost to the military, as there is no return on investment for students dropped from training.

IX. RESULTS

To validate the model, we used backward-looking analysis as the forward-looking analysis was not used to generate the graduation prediction tool. Using the backward-looking approach and results from Tables 6 and 9 at the .5 threshold, we conclude that the graduation prediction model currently in use at NAVSCOLEOD is not within the specified requirements of NAVSCOLEODINST 5420.1U. The updated data in Table 9 shows that of all the students who graduated and experienced a training setback, the model predicted 94.1% would graduate and 5.9% would fail. Although these percentages are close, they do not meet the minimum threshold of the graduation prediction model requirements of 95% and 5 percent. It is up to NAVSCOLEOD to decide whether this level of error is acceptable.

In addition, the updated data from Table 9 shows students are still given the benefit of the doubt from the decision tool. Of all students who fail, the model predicted 75.7% would graduate (this is a false alarm). The model will most likely retain a student, when he or she will actually fail. This false alarm rate is much higher than in the original ARB Probability Matrix in Table 2, which predicts only a 27% false alarm rate, while updated data predicts a 75.7% false alarm rate. While the updated percentage reflects a more conservative approach, there is a monetary cost associated with this.

When the threshold is lowered to .4, we can see, as expected, the improvement in graduation prediction. The updated data from Table 12 shows that of all the students who graduate and experience a training setback, the model predicted 97.2% would graduate and 2.8% would fail. Although this is an improvement from the .5 threshold, it does not meet the criteria of the instruction. The model validation in Table 4 (FY05) predicted successful completion of training for 100% of the graduates who experienced a setback when the threshold is lowered. We can see that current data did not predict 100%, although it is within 4% of that lowered decision threshold. It is up to the chain of command at EOD School to determine if this variation is acceptable.

Overall, rates based on current data are close to those in the criteria outlined in NAVSCOLEODINST 5420.1U. Points of concern include a higher false-alarm rate and variations at the .5 and .4 thresholds.

A. NUMBERS BY THE YEARS

After we looked at a large sample size (*n* = 1495) over the years 2004–2008, we wanted to examine each year more specifically to see how much variation existed from year to year. This would enable us to determine if variations from the instruction criteria of 95% and 5% existed in all years, or if one year produced enough variation to skew the entire data set. Tables 14 through 28 reflect data from each year.

1. Year 2004

Table 14. 2004 Student Setback Data (Threshold = .5)

	Graduated		
Prediction	Yes	No	Total
Yes	173	67	240
No	20	29	49
Total	193	96	289

Table 15. 2004 Backward-Looking Analysis

	Graduated	
Prediction	Yes	No
Yes	89.6%	69.8%
No	10.4%	30.2%
Total	100.00%	100.00%

Of all the students who graduated and experienced a setback, 89.6% were predicted to graduate, while 10.4% were predicted to fail. These results are similar to our overall findings regarding the backward-looking approach.

Table 16. 2004 Forward-Looking Analysis

Prediction	Graduated Yes	No	Total
Yes	72.1%	27.9%	100.00%
No	40.8%	59.2%	100.00%

Of all the students who were predicted to fail, 40.8% of them actually succeeded. Simply, two out of every five students that were predicted to fail would have actually graduated. These results are farther from the instruction criteria than the overall findings of 31.9% regarding the forward-looking approach.

2. Year 2005

Table 17. 2005 Student Setback Data (Threshold = .5)

Prediction	Graduated Yes	No	Total
Yes	193	101	294
No	20	60	80
Total	213	161	374

Table 18. 2005 Backward-Looking Analysis

Prediction	Graduated Yes	No
Yes	90.6%	62.7%
No	9.4%	37.3%
Total	100.00%	100.00%

Of all the students who graduated and experienced a setback, 90.6% were predicted to graduate, while 9.4% were predicted to fail. This data is similar to our overall findings regarding the backward-looking approach.

Table 19. 2005 Forward-Looking Analysis

Prediction	Graduated Yes	No	Total
Yes	65.6%	34.4%	100.00%
No	25.0%	75.0%	100.00%

Of all the students who were predicted to fail, 25% of them actually succeeded. Simply, one out of four students that were predicted to fail would have actually graduated. These results are closer to the instruction criteria than the overall findings of 31.9% regarding the forward-looking approach.

3. Year 2006

Table 20. 2006 Student Setback Data (Threshold = .5)

Prediction	Graduated Yes	No	Total
Yes	175	62	237
No	10	16	26
Total	185	78	263

Table 21. 2006 Backward-Looking Analysis

Prediction	Graduated Yes	No
Yes	94.6%	79.5%
No	5.4%	20.5%
Total	100.00%	100.00%

Of all the students who graduated and experienced a setback, 94.6% were predicted to graduate while 5.4% were predicted to fail. These results are closer to the instruction criteria than our overall findings regarding the backward-looking approach.

Table 22. 2006 Forward-Looking Analysis

	Graduated		
Prediction	Yes	No	Total
Yes	73.8%	26.2%	100.00%
No	38.5%	61.5%	100.00%

Of all the students who were predicted to fail, 38.5% of them would have succeeded. These results are further from to the instruction criteria than our overall findings of 31.9% regarding the forward-looking approach.

4. Year 2007

Table 23. 2007 Student Setback Data (Threshold = .5)

	Graduated		
Prediction	Yes	No	Total
Yes	271	78	349
No	6	14	20
Total	277	92	369

Table 24. 2007 Backward-Looking Analysis

	Graduated	
Prediction	Yes	No
Yes	97.8%	84.8%
No	2.2%	15.2%
Total	100.00%	100.00%

Of all the students who graduated and experienced a setback, 97.8% were predicted to graduate, while 2.2% were predicted to fail. These results are much closer to the instruction criteria than our overall findings regarding the backward looking approach.

Table 25. 2007 Forward-Looking Analysis

Prediction	Graduated Yes	No	Total
Yes	77.7%	22.3%	100.00%
No	30.0%	70.0%	100.00%

Of all the students who were predicted to fail, 30% of them actually succeeded. These results are closer to the instruction criteria than our overall findings regarding the forward-looking approach.

5. Year 2008

Table 26. 2008 Student Setback Data (Threshold = .5)

Prediction	Graduated Yes	No	Total
Yes	115	78	193
No	2	5	7
Total	117	83	200

Table 27. 2008 Backward-Looking Analysis

Prediction	Graduated Yes	No
Yes	98.3%	94.0%
No	1.7%	6.0%
Total	100.00%	100.00%

Of all the students who graduated and experienced a setback, 98.3% of them had a model score of .5 or higher, while 1.7% had a model score lower than .5. The prediction for graduation was very accurate; however, the false-alarm rate was extremely high. The model kept 94% of students who would not graduate.

Table 28. 2008 Forward-Looking Analysis

Prediction	Graduated Yes	No	Total
Yes	59.6%	40.4%	100.00%
No	28.6%	71.4%	100.00%

Of all the students who were predicted to fail, 28.6% of them actually succeeded. The rate of correctly predicting failure was higher in this year than in any other, while predicting success was roughly 60:40.

B. SERVICE-SPECIFIC ANALYSIS

For further analysis, we examined each service specifically from years 2004–2008 with regards to the research question, "Is the model valid?" We wanted to determine if each service followed the criteria in the NAVSCOLEODINST 5420.1U, or if there were variations among branches of the military. Additionally, this would bring to the forefront any red flags in a particular service that deviated from the norm. For each branch, we compared the specific setback group first against the overall student body, and then we examined setbacks only within each service. For example, we compared Army setbacks against setbacks from all services school-wide. Then, we looked at only Army setbacks within their own service. This is important because although the Army may have ownership of over 50% of all students who experience a setback, they also have the largest population at EOD School.

We began with a sample size of 1,495. This sample included all students who attended EOD School from 2004–2008 and experienced at least one academic setback. Students who experienced setbacks for security, medical, administrative, or any other reason were filtered out. In addition, their student status was terminated for only one of two reasons; the student either graduated or was dropped from training for an academic reason. All other training terminations, such as behavioral, Drop on Request (DOR), medical, etc. were also filtered out. Finally, we removed students that we determined were dropped because they had low model scores, since those students never had the opportunity to continue and graduate.

1. Overall School Statistics

Of all students in our filtered subset who experienced an academic setback from 2004–2008, 52.7% were from the United States Army (USA), 22.7% were from the United States Air Force (USAF), 10.3% were from the United States Marine Corps (USMC) and 13.5% were from the United States Navy (USN).

Breaking these numbers down further into two groups, students who graduate and students who do not graduate, gives us more insight into service-specific differences. Of all students who experience at least one academic setback and do not graduate, 53.6% are USA, 26.3% are USAF, 6.0% are USMC and 13.5% are USN. The remaining 0.6% belongs to civilians attending EOD School (the Coast Guard does not have EOD assets).

Of all students in our filtered subset who experience at least one academic setback and do graduate, 52.1% are USA, 20.6% are USAF, 12.9% are USMC and 13.5% are USN. The remaining 0.8% belongs to civilians attending EOD School. Although this interesting, a more accurate picture of service specific trends is found by examining each student setback rate against its own service population.

2. U.S. Army

Of all Army students who experience a setback, with no regard to model score, 34.6% of those students did not graduate, while 65.4% did. The number of students of each sort is show in Table 29. However, with use of the graduation prediction model, we can more accurately identify which students fit into the graduation and non-graduation categories. Using the backward-looking analysis in NAVSCOLEODINST 5420.1U, we see that of all USA students who graduated and experienced a setback, the model predicted the success of 98.1% of those students, while only "missing" 1.9% (Table 30). This is within the instruction standards of 95% and 5% regarding backward-looking analysis.

The right hand side of the table reveals the false-alarm rate; of the students who failed out of school, the model predicted that 87.1% of those students *would* graduate. This represents a "benefit of the doubt" to students, but is a cost lost to the Army.

Table 29. 2004–2008 U.S. Army Data

Prediction	Graduated Yes	No	Total
Yes	490	220	710
No	24	52	76
Total	514	272	786

Table 30. 2004–2008 Backward-Looking Analysis

Prediction	Graduated Yes	No
Yes	98.10%	87.10%
No	1.90%	12.90%
Total	100.00%	100.00%

The forward-looking analysis (Table 31) produces different statistics. Of all Army students who were predicted to graduate, 69% of those students actually graduated. However, of all Army students who were predicted to fail, 31.6% of those students actually graduated. Among students who would have been dropped by the model, over 30% would have graduated and become EOD technicians.

The right hand side of the table reveals the false-alarm rate; among students with setbacks predicted to graduate by the model, 31% eventually failed out of training. This number is more accurate than the 87.1% calculated above.

Table 31. 2004–2008 Forward-Looking Analysis

Prediction	Graduated Yes	No	Total
Yes	69.0%	31.0%	100.00%
No	31.6%	68.4%	100.00%

Looking at Table 29, we see that there were only 24 students in five years (2004–2008) that the model predicted would not graduate but in fact did. Similarly small sample sizes appear in each service-specific table. Taking into account all the aforementioned filters, the reason for such a small sample size in this block is reflective of the model itself. The purpose of the graduation prediction model is to terminate from training a student who has a low probability of graduation. This decision is based on his or her model score. Therefore, the standard is that if a student possesses a low model score (below the .4 or .5 threshold) he or she will be removed from training. It makes sense then that this sample size is small as almost all of the students that the model predicted would not graduate were then removed from training and are absent in our data set.

However, the number 76 in the second row of Table 29 shows that procedure was not always followed. A few students who had low model scores were allowed to continue training. This allows us to examine how they progressed through school. Therefore, although this number is small, it gives us some valuable insight into how students with low model scores would have actually done given the opportunity to continue in school. As it turns out, across all services 31.9% of students with low model scores actually went on to graduate.

3. U.S. Air Force

Of all Air Force students who experienced a setback, with no regard to model score, 40.5% of those students did not graduate, while 59.5% did graduate. The number of students of each sort is shown in Table 32. Using the backward looking analysis in NAVSCOLEODINST 5420.1U, of all USAF students who graduated and experienced a setback, the model predicted the success of 97% of those students, while only missing 3% (Table 33). The right hand side of the table reveals the false-alarm rate; of the students who failed out of school, the model predicted that 83.3% of those students *would* graduate. This represents a "benefit of the doubt" to students, but is a cost lost to the Air Force.

Table 32. 2004–2008 U.S. Air Force Data

	Graduated		
Prediction	Yes	No	Total
Yes	186	103	289
No	17	35	52
Total	203	138	341

Table 33. 2004–2008 Backward-Looking Analysis

Prediction	Graduated Yes	Graduated No
Yes	97.00%	83.30%
No	3.00%	16.60%
Total	100.00%	100.00%

The forward-looking analysis, (Table 34) produces different statistics. Of all Air Force students who were predicted to graduate, 64.6% of those students actually graduated. However, of all Air Force students who were predicted to fail, 32.7% of those students actually graduated. This is a much larger number than the 4% presented in the backward-looking analysis. This is because these numbers represent different ratios. Among students who would have been dropped by the model, 32.7% graduated and became EOD technicians. The right hand side of the table reveals the false-alarm rate; among students with setbacks predicted to graduate by the model, 35.4% eventually failed out of training. This number is a better indicator of the model's inaccuracy than the 83.3% calculated above.

Table 34. 2004–2008 Forward-Looking Analysis

Prediction	Graduated Yes	Graduated No	Total
Yes	64.40%	35.40%	100.00%
No	32.70%	67.70%	100.00%

4. U.S. Marine Corps

Marine Corps students who experienced a setback had the highest probability of graduating among students from all the services. With no regard to model score, 81.4% of those students graduate, while only 18.6% do not graduate. The number of students of each sort is shown in Table 35. Using the backward looking analysis in NAVSCOLEODINST 5420.1U, we can see that of all USMC students who graduated and experienced a setback, the model predicted the success of 94.5% of those students, while only missing 5.5% (Table 36). The right hand side of the table reveals the false-alarm rate; the model predicted that a student *would* graduate in 55.2% of setback cases, when in fact the student eventually failed out of training. This represents a "benefit of the doubt" to students, but is a cost lost to the Marine Corps.

Table 35. 2004–2008 U.S. Marine Corps Data

	Graduated		
Prediction	Yes	No	Total
Yes	120	16	136
No	7	13	20
Total	127	29	156

Table 36. 2004–2008 Backward-Looking Analysis

	Graduated	
Prediction	Yes	No
Yes	94.50%	55.20%
No	5.50%	44.80%
Total	100.00%	100.00%

The forward-looking analysis (Table 37) produces different statistics. Of all Marine Corps students who were predicted to graduate, 88.2% of those students actually graduated. However, of all Marine Corps students predicted to fail, 35% actually graduated and became EOD technicians. The right hand side of the table reveals the false-alarm rate; among students with setbacks predicted to graduate by the model, 11.8% eventually failed out of training. This number is a better indicator of the model's inaccuracy than the 55.2% calculated above.

Table 37. 2004–2008 Forward-Looking Analysis

	Graduated		
Prediction	Yes	No	Total
Yes	88.20%	11.80%	100.00%
No	35.00%	65.00%	100.00%

5. U.S. Navy

Of all Navy students who experienced a setback, with no regard to model score, 33.5% of those students did not graduate, while 66.5% did. The number of students of each sort is shown in Table 38. Using the backward looking analysis in NAVSCOLEODINST 5420.1U, we can see that of all USN students who graduated and experienced a setback, the model predicted the success of 92.5% of those students, while missing 7.5% (Table 39). The right hand side of the table reveals the false-alarm rate; the model predicted that a student *would* graduate in 68.7% of setback cases, when the student would eventually fail out of training. This represents a "benefit of the doubt" to students, but is a cost lost to the Navy.

Table 38. 2004–2008 U.S. Navy Data

	Graduated		
Prediction	Yes	No	Total
Yes	123	46	169
No	10	21	31
Total	133	67	200

Table 39. 2004–2008 Backward-Looking Analysis

	Graduated	
Prediction	Yes	No
Yes	92.50%	68.70%
No	7.50%	31.30%
Total	100.00%	100.00%

The forward-looking analysis (Table 40) produces different statistics. Of all Navy students who were predicted to graduate, 72.8% of those students actually graduated. However, of all Navy students who were predicted to fail, 32.3% actually graduated. Among students who would have been dropped by the model, over 30% graduated and became EOD technicians. The right hand side of the table reveals the false-alarm rate; among students with setbacks predicted to graduate by the model, 27.2% eventually failed out of training. This number is a better indicator of the model's inaccuracy than the 68.7% calculated above.

Table 40. 2004–2008 Forward-Looking Analysis

	Graduated		
Prediction	Yes	No	Total
Yes	72.80%	27.20%	100.00%
No	32.30%	67.70%	100.00%

6. Service Results

With regards to our original research question, “Is the model valid?” it appears that when the data is broken down by service the model still holds for the USA and the USAF. However, the USMC and USN are just outside the instruction requirements of predicting 95% of graduates and missing 5 percent. We must remember the caveat that there are two ways to interpret the data: the backward-looking approach and the forward-looking approach. These results are based on the backward-looking approach, since that is what the model was built on.

The NAVSCOLEODINST 5420.1U uses the backward-looking analysis, claiming it predicts successful graduation in 95% of student setback cases, while only missing 5% at the .5 threshold. When broken down by service, the USA and USAF meet those criteria. The model predicts successful graduation in 98.1% of Army setbacks while only missing 1.9%. It predicts successful graduation in 97% of Air Force setbacks while only missing 3%. However, the USMC and USN are outside the instruction standards. The model predicts 94.5% of Marine Corps graduates and 92.5% of Navy graduates while only missing 5.5% and 7.5%, respectively. However, to be fair, the instruction is joint for the entire school.

Analyzing the data from 2004–2005 with the forward-looking approach, we see that of the students who were predicted to graduate across all services, 73.5% actually graduated, while 26.5% did not. However, of the students who predicted to fail, 69% actually failed, while 31% went on to graduate. Overall, the model accurately predicted the end result in 72.6% of setback cases. It incorrectly predicted the end result in 27.4%

of setback cases. Breaking this down by service, there is a greater deviation from these parameters. The following show the comparison between the services and the figures for all of the services combined:

> Army—Of the students who were predicted to graduate, 69% actually graduated, while 31% did not. Of the students who were predicted to fail, 68.4% actually failed while 31.6% went on to graduate. Overall, the model accurately predicted the end result in 69% of setback cases. It incorrectly predicted the end result in 31% of setback cases
>
> Air Force—Of the students who were predicted to graduate, 64.4% actually graduated while 35.6% did not. Of the students who were predicted to fail, 67.7% actually failed while 32.3% went on to graduate. Overall, the model accurately predicted the end result in 64.8% of setback cases. It incorrectly predicted the end result in 35.2% of setback cases
>
> Marine Corps—Of the students who were predicted to graduate, 88.2% actually graduated while 11.8% did not. Of the students who were predicted to fail, 65% actually failed while 35% went on to graduate. Overall, the model accurately predicted the end result in 85.3% of setback cases. It incorrectly predicted the end result in 14.7% of setback cases
>
> Navy—Of the students who were predicted to graduate, 72.8% actually graduated while 27.2% did not. Of the students who were predicted to fail, 67.7% actually failed while 32.3% went on to graduate. Overall, the model accurately predicted the end result in 72% of setback cases. It incorrectly predicted the end result in 28% of setback cases

No service matches our 2004–2005 overall data findings regarding the forward-looking approach. For example, the Marine Corps far exceeds our finding in correctly predicting graduation, but falls short in accurately predicting failures. The best way to analyze the service-specific data is to compare the percentages of how often the model accurately predicted the end result. The model was the most accurate in predicting Marine Corps success or failure, while it was least accurate for the Air Force.

C. SETBACKS BY DIVISION

We also examined the number of setbacks in each division from years 2004–2008. This analysis will help future researchers determine if a more accurate regression equation could be developed to account for where the student's setback occurred in school. In the current equation, the student's setback division (1–12) is multiplied by a coefficient (0.032) to generate the model score. Since the divisions increase in number from 1 to 12, a student is more likely to succeed for every division that student passes. The model score increases by an equal increment for each division. However, this equal increase assumes that each division is equally difficult. We calculated the number of failures in each division to analyze where students had their setbacks for the years between 2004 and 2008. During these years, there were a total of 1,559 setbacks. The following graph in Figure 3 represents our results.

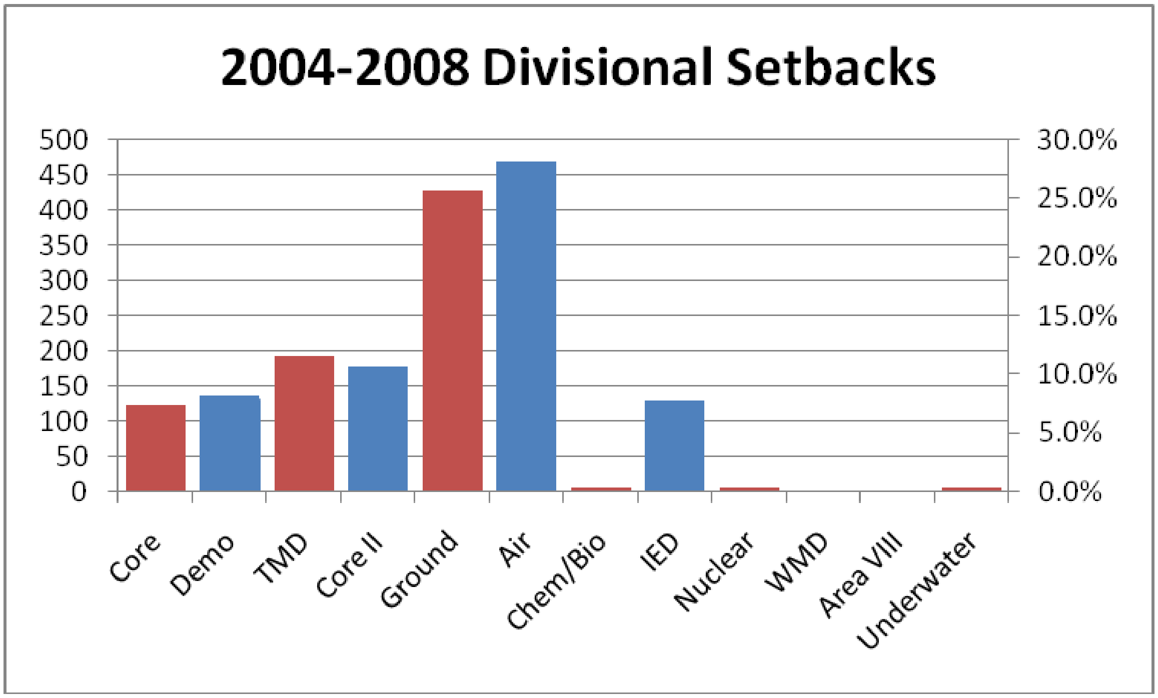

Figure 3. Divisional Setbacks

There were students who are set back in the Chem/Bio, Nuclear, WMD, Area VIII and Underwater divisions; their percentages are just too small to display on the graph. As the graph shows, the number of setbacks generally increases through Air Division and then drops off drastically. A more accurate model score might be computed by adjusting the setback coefficient to reflect this information.

D. NON-ACADEMIC TERMINATIONS

Going back to our original unabridged data set, we also analyzed the non-academic terminations between the years 2004 and 2008. Since man-hours and money can be saved with an accurate prediction model, the military could experience similar cost savings by focusing on the non-academic terminations as well. The following graphs represent reasons for student termination from EOD School excluding academic reasons. During this time period, 1,287 students were removed from school for non-academic reasons out of 5,075 total students who attended school.

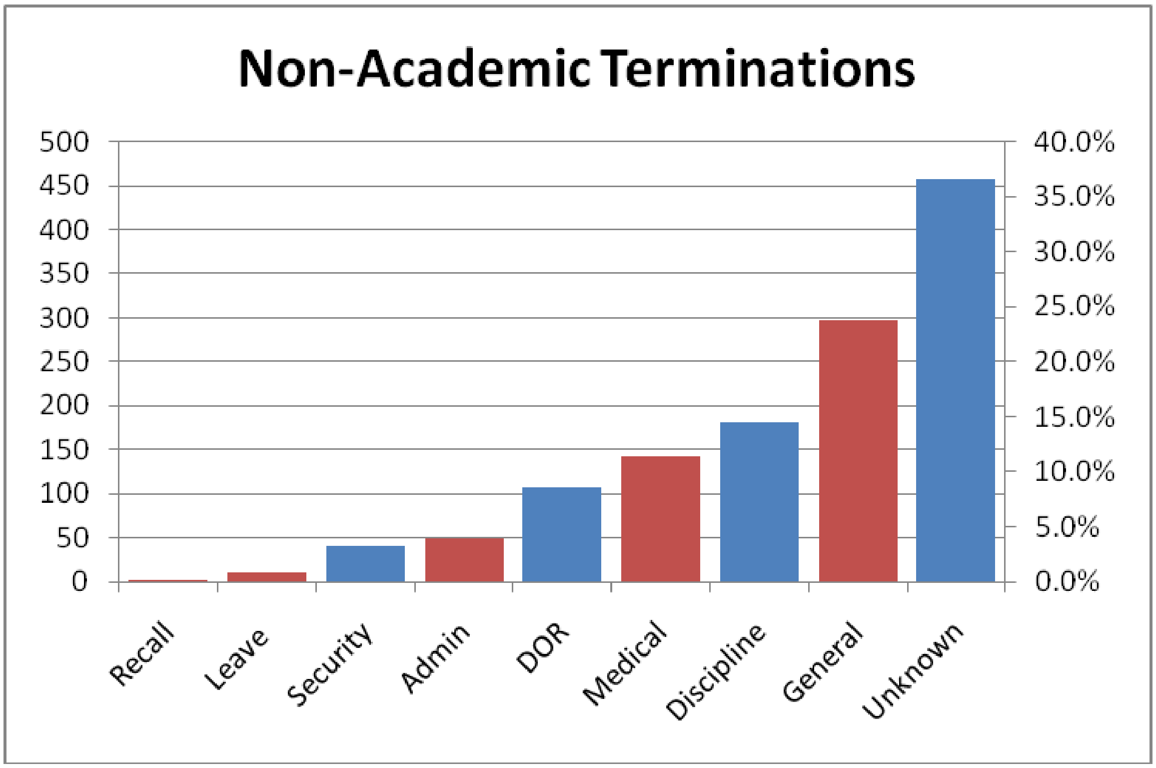

Figure 4. Non-Academic Terminations

Since 25% of students terminate training for non-academic reasons, a further examination of these incidents could result in lower attrition rates and cost savings. In addition, “unknown” and “general” reasons reflected the highest percentages of non-academic terminations. More specific data would provide greater insight into these termination categories.

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X. CONCLUSION

The purpose of this MBA Project was to determine if a student's Grade Point Average (GPA) while attending Naval School Explosive Ordnance Disposal (NAVSCOLEOD) would be an accurate predictor of graduation. NAVSCOLEDOINST 5420.1U claims that the model predicts successful completion of training for 95% of graduates who experienced a setback, and that the model is far more accurate overall than the traditional ARB process. Based on updated student data from 2004–2008, the model predicted 94.1% would graduate and 5.9% would fail. Although this is not within the specified requirements of NAVSCOLEODINST 5420.1U, the numbers are similar and stakeholders must determine what constitutes a significant deviation from the expected model probabilities listed in Table 2.

We also conclude that the backward-looking analysis used in the graduation prediction model is not an accurate portrayal of whether a student will succeed or fail. That analysis proceeds from outcome to prediction, instead of the other way around. The forward-looking analysis is a more logical approach. First, the prediction is made and then the outcome of graduation or failure follows. This approach allows us to decide if the prediction was correct at the time of setback.

We claim that the backward-looking approach does not produce a true picture of student success or failure. There is a much smaller error statistic associated with this analysis than with to the forward-looking approach. We claim the forward-looking approach produces data that is more reflective of what is actually occurring at NAVSCOLEOD. A larger percentage of students who would actually continue on to graduate are being dismissed from training than what the backward-looking approach leads one to believe.

We recommend that the forward-looking approach be the method of choice to view student setback data. However, to produce the 95% prediction success rate as claimed in NAVSCOLEODINST 5420.1U, a new model must be developed. Simply lowering the threshold in the backward-looking approach will result in an increase in prediction success. This was evident in Section VIII, Lowering the Threshold. However, to reiterate, the backward-looking approach is not an accurate portrayal of student graduation or failure.

However, lowering the threshold in the forward-looking approach will guarantee neither an increase nor a decrease in prediction success, due to the difference in ratios. A new model will determine if the prediction criteria of 95% at the time of setback is achievable. The current model cannot be manipulated to produce these figures. A follow-up thesis will address these issues. A graduation prediction tool at NAVSCOLEOD is vital; the model conserves numerous man-hours that would be lost to the ARB process. With student throughput increasing 44% from 2004 to 2008, an accurate model will be a critical tool to handle the hundreds of student setbacks that occur every year.

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